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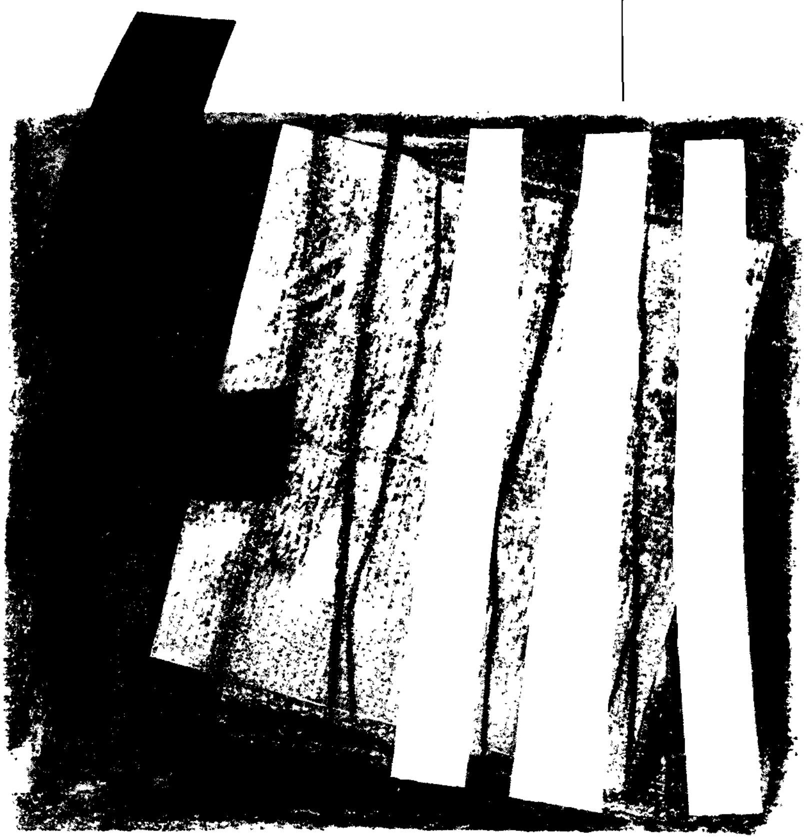

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FORECASTING MONETARY UNION INFLATION: A DISAGGREGATED APPROACH BY COUNTRIES AND BY SECTORS.

A. Espasa, E. Senra and R. Albacete*

Abstract

Inflation in the European Monetary Union is measured by the Harmonised Consumer Price Index (HCPI) and it can be analysed by breaking down the aggregate index in two different ways. One refers to the breakdown into price indexes corresponding to big groups of markets throughout the European countries and another considers the HCPI by countries. The paper shows that both disaggregations are of interest because in each one, the component prices are not fully cointegrated and then have more than one common factor. For purposes of forecasting the HCPI for the global EMU the disaggregation matters in all the horizons, one to twelve months, considered in the paper. The question is that innovations in an aggregate of non-fully cointegrated componentes will have different long-run effects depending on the common trend which they mainly stem from. Then the resulting ARIMA model for the aggregate can have a quite complex structure which restrictions which could be captured more easily through a disaggregate approach.

Keywords: core inflation; cointegration; univariate models; VeqCM.

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1. Introduction

Inflation in the Monetary Union is measured by the Harmonised Consumer Price Index (HCPI) and it can be analysed by breaking down the aggregate index in two different ways. One refers to the breakdown into price indexes corresponding to large groups of markets (sectors) throughout the European countries and another considers the HCPI by countries. Both disaggregations are of interest because in each one, as is shown in the paper, the different components prices are not fully cointegrated. The absence of full cointegration between the n elements of a vector time series implies that the trends in the component time series are generated by more than one common factor. Consequently the innovations in the aggregate will have different long-run effects depending on the common trend which they mainly stem from. The lack of full cointegration also points out that there is no full convergence between the components.

Having detected that the breakdown by groups of markets matters, and that disaggregation by countries is also required, one could study the aggregate inflation by considering a price index for each big group of markets in each country. But eleven countries by six or seven markets groups makes for a large number of components, and before facing such an approach, in this paper we start by considering the two mentioned disaggregation possibilities separately. Our aim is to evaluate their relevance for forecasting and policy analysis and to get, at the same time, an indication of how to proceed in a further study when we work with a breakdown that joins both criteria.

In this paper the breakdown of HCPI by markets is approached taking into account theoritical considerations about differences in supply and demand, which could result in prices having different trends. This leads us to consider, at least, the following price indexes corresponding to: (1) Non Processed Food, (2) Energy, (3) Other Goods and (4) Other services. For this vector of four elements, the number of cointegration relationships is less than three and, therefore, there is more than one common trend between them. Based on this result, the paper gives empirical evidence that the forecast of the HCPI is more accurate by forecasting the components and then aggregating the forecasts, than by aggregating first and forecasting the aggregate directly.

The above study by markets also shows that the price indexes (1) and (2) are more volatile than (3) and (4). Then for the purpose of presenting results it turns out to be useful to split the HCPI inflation in two, with the inflation coming from indexes (1) and (2) being denoted as residual, and the inflation coming from (3) and (4) being denoted as core inflation. The paper argues that the important question in the short-term analysis of inflation is to have good forecasts on which to base possible policy recommendations and the distinction between residual and core inflation is just an instrument for presenting results which in occasions is useful. But since the price index on which the residual inflation is obtained is not cointegrated with the price index used to calculate core inflation, the projections of the latter index are not always a good proxy for forecasts of overall HCPI.

The analysis by countries is performed working only with France, Germany, Italy and Spain whose global weight in the Euro-zone inflation is 83%. With four countries, it is possible to analyse cointegration between them and, as happens in the study by markets, there is no full cointegration amongst them. The lack of full cointegration appears as an indicator of convergence problems within MU.

The article is organised as follows. Section 2 describes the statistical integration and cointegration properties of Harmonised Consumer Price Indexes and develops univariate and multivariate models for the disaggregations by countries and by sectors. Section 3 analyses the forecasting performance of the proposed models and, lastly, section 4 concludes and provides forecasts and a diagnosis for MU inflation in 2000 and 2001.

2. Statistical description of Harmonised Consumer Price Index time series: Integration and cointegration analysis.

Harmonised Consumer Price Indexes (HCPI) are published by Eurostat by means of two different disaggregation patterns. The first one corresponds to the disaggregation by countries and the second one to the breakdown in different markets for each country and for the Monetary Union (MU) in global. This last information set is formed approximately by 130 subindexes, which considered in eleven countries sum up 1430 different time series to analyse.

It is necessary then to simplify the information set not avoiding to include neither the information relative to the countries, nor the corresponding to the sectors. The approach taken in this study considers:

(1) The global HCPI for each country.
(2) Five basic sectors for the Monetary Union (MU). These components come from the four ones mentioned in the previous section dividing the (3) component, "Other goods", in food, denoted as "processed food", and the rest, denoted as "commodities".

Since Eurostat is still improving the methodology in the calculation of HCPI and making revisions of the current and historical data (for example, in the indexes corresponding to the prices of commodities and services these revisions have a magnitude up to four decimal points in some specific moments for MU, Germany, France and Spain; in the global HCPI of each country there are less revisions); the sample used in this article corresponds to the revised figures from January 1995 to July 2000 published in August 2000. There exist longer time series since January 1990, but data for the period 1990-1995 are not reliable. The current sample for MU and Germany HCPI is available only since January 1996. Previously Eurostat published some figures for 1995 that are now under revision. Therefore, the rates for 1995 have been used to construct a time series for MU and Germany HCPI since January 1995. The data can be found at the appendix (tables A1 and A2).

2.1 Analysis by countries

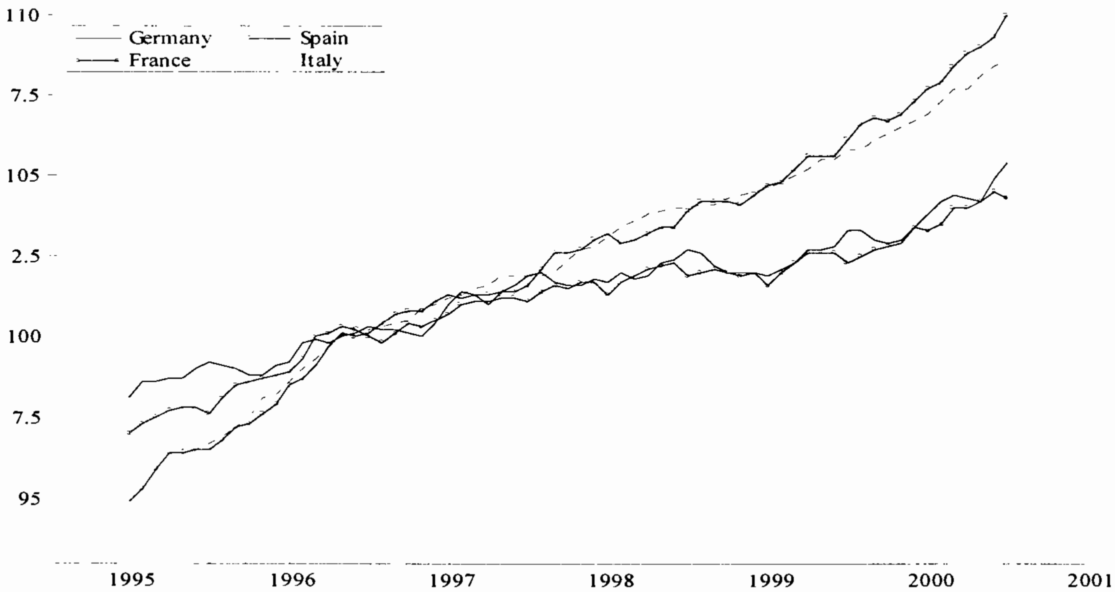
Table 1 shows the weights for different MU countries in the calculation of HCPI, corresponding to year 2000.

Table 1: Country weights in MU	
Country	**Weight (2000)**
Austria	2.91%
Belgium	3.99%
Finland	1.51%
France	20.91%
Germany	34.65%
Ireland	0.98%
Italy	18.31%
Luxembourg	0.20%
Portugal	1.81%
Spain	9.08%
MU	100%
Source: Eurostat	

This table shows that four countries: Germany, France, Italy and Spain, sum up 82.95% of total MU weight. Given the scarce number of observations available, it has been necessary to further simplify the statistical analysis and those four countries are the only ones, which we are going to take into consideration.

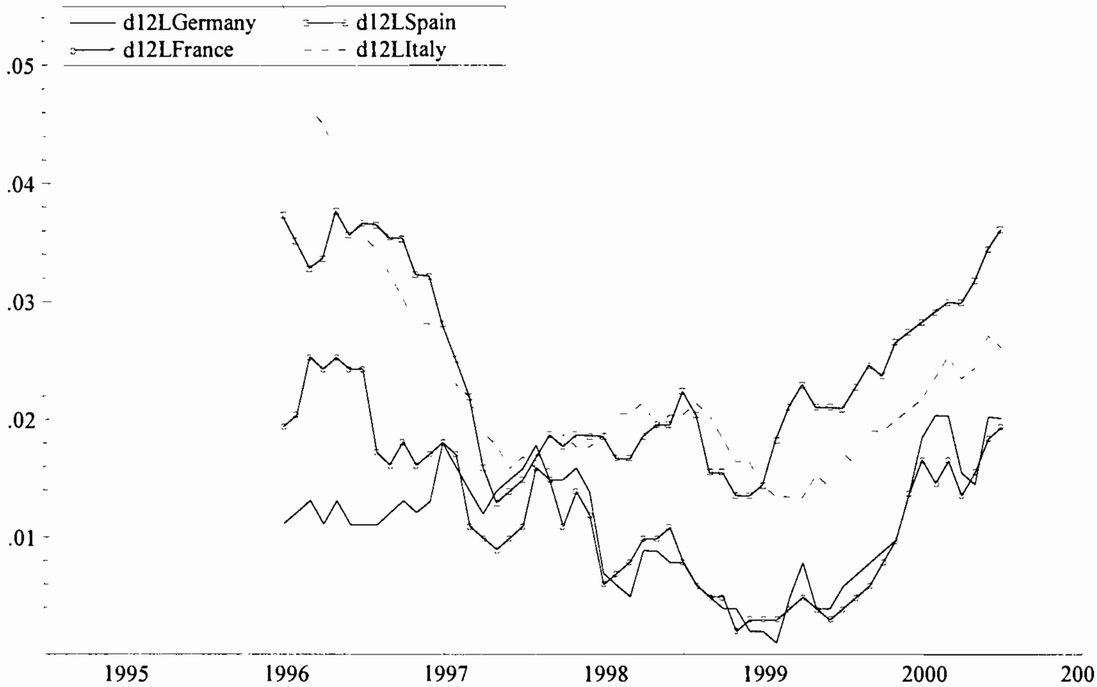
Graphs of the four indexes can be found in figures 1A and 1B.

Figure 1A: Harmonised Consumer Price Indexes



Source: Eurostat

Figure 1B: Annual rates of HCPI in different countries (annual difference of logs –d12L–)



Source: Eurostat

Before modelling the HCPIs, it is useful to determine the orders of integration for the four variables considered. Table 2 lists order augmented Dickey-Fuller (1981) statistics for the variables.

Table 2: ADF statistics for testing for a unit root

Null Order	Germany	France	Italy	Spain
I(1)	0.33 (0.007)	-0.14 (-0.003)	0.36 (0.002)	1.36 (0.01)
I(2)	-5.56** (-1.19)	-4.34** (-0.98)	-3.41* (-0.73)	-3.54* (-0.57)

Notes: (1) Here and elsewhere in this paper, asterisks * and ** denote rejection at the 5% and 1% critical values. The critical values for this table are calculated from MacKinnon (1991).

(2) The results here presented are obtained from PC-GIVE 9.0
(3) Series are taken in logs.
(4) Values reported are the first-order (k=1) augmented Dickey-Fuller statistics and in parentheses the estimated coefficient on the lagged variable x_{t-1}

Unit root tests are reported for the original variables in logs and for their first differences. Empirically, all variables appear to be integrated of order 1 -I(1)- with the hypothesis of second unit root being rejected[1].

Cointegration analysis helps to clarify the long-run relationships between integrated variables. Johansens' (1988, 1991) procedure for finite-order vector autoregressions (VARs) is applied here. Given the scarce number of observations, the analysis began with a VAR model in levels of order 5 with a constant term and seasonal dummies which was then reduced to a first-order VAR. Table A3 in appendix shows that it is statistically acceptable.

Table 3 reports the standard statistics and estimates for Johansen's procedure applied to this first-order VAR. The greatest eigenvalue and trace eigenvalue statistics (λ_{max} and λ_{trace}) reject the null of no cointegration in favour of one cointegrating relationship.

Table 3: A cointegration analysis of global HCPI by countries.

Eigenvalue	0.706	0.289	0.088	0.014
Null Hypotesis	r=0	r≤1	r≤2	r≤3
λ_{max}	72.18**	20.09	5.46	0.82
λ_{max}^{a}	67.29**	18.73	5.09	0.76
95% critical value	27.1	21.0	14.1	3.8
λ_{trace}	98.55*	26.37	6.28	0.82
λ_{trace}^{a}	91.87**	24.58	5.85	0.76
95% critical value	47.2	29.7	15.4	3.8
	Standardized eigenvectors β'			
Variable	Germany	Spain	France	Italy
	1	1.67	-1.53	-1.69
	-1.38	1	2.40	-1.54
	-11.1	4.01	1	0.34
	-0.71	-1.95	1.99	1
	Weak exogeneity test statistics			
Variable	Germany	Spain	France	Italy
$\chi^2(1)$	0.11	6.16*	1.13	49.51**
p-value	[0.74]	[0.01]	[0.29]	[0.00]

Figure 2 shows the cointegration vector corresponding to the greatest eigenvalue.

[1] These results could be due to the fact that we are working with a small sample. With longer time series it could appear that price indexes are I(2) or I(1) with segmented means (see Lorenzo (1997) for the Spanish case).

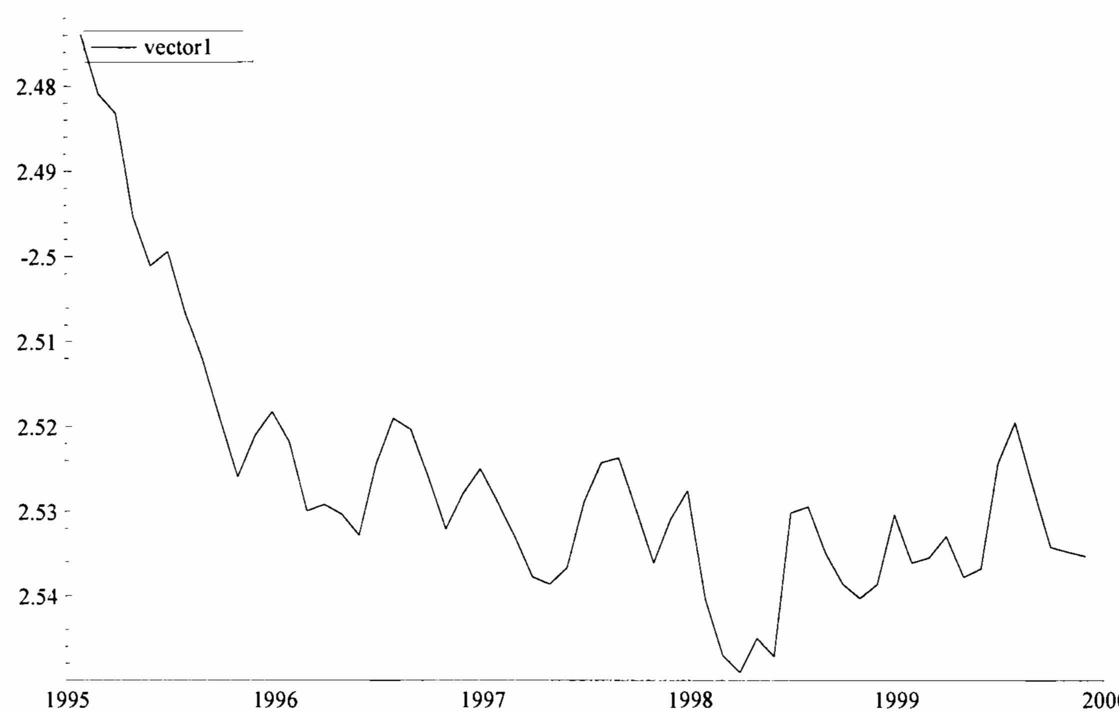


Figure 2: Cointegration relationship corresponding to the greatest eigenvalue

The estimated cointegration relationship could be written as:

log(HCPI Germany) – 1.53 log(HCPI France) = 1.69 log(HCPI Italy)-1.67 log(HCPI Spain)

Thus, the long run equilibrium equation equals some sort of weighted price differential between countries with high level of prices (France and Germany) with the price differential for countries with lower levels (Italy and Spain). These results indicate the lack of full cointegration between HCPI in different countries and, therefore, shows the existence of more than one common trend between them.

A Vector Autoregression Model with Equilibrium-Correction Mechanism for the four countries has been estimated and results are shown in table 4. The model also includes seasonal dummies and CI_t represents the cointegration relationship.

Table 4: VEqCM model for countries.

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & (1\text{-}0.38L) & 0 \\ 0.21L & 0 & -0.24L & (1+0.29L) \end{pmatrix} \begin{pmatrix} \Delta\log \text{Germa}_t \\ \Delta\log \text{France}_t \\ \Delta\log \text{Spain}_t \\ \Delta\log \text{Italy}_t \end{pmatrix} - \begin{pmatrix} 0.0009 \\ 0.0010 \\ 0.0012 \\ 0.2600 \end{pmatrix} -$$

$$- \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0.10L \end{pmatrix} CI_t = \begin{pmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \\ a_{4t} \end{pmatrix}$$

The residual standard deviation for each equation is shown later in table 7 and the contemporaneous correlation matrix for the residuals is given in table 5. The biggest correlations are between Germany and France and, Spain and Italy.

Table 5: Correlation matrix of residuals				
	Δlog Germany	**Δlog France**	**Δlog Spain**	**Δlog Italy**
Δlog Germany	1			
Δlog France	0.50	1		
Δlog Spain	0.35	0.27	1	
Δlog Italy	0.13	-0.006	0.38	1

This model shows (1) there is just one long run equilibrium relationship that only enters in the equation for Italy and (2) there is not much dependence between the variables in the short run. The last point is confirmed by the cross correlograms of the residuals. This VEqCM model points out that a disaggregating analysis of HCPI by countries could be carried out without too much distortion – except, perhaps, for the case of Italy – by separate single-equation models. For forecasting purposes then ARIMA models or ARIMA models with leading indicators could be used.

Univariate models for these four countries are summarised in table 6.

Table 6: Univariate ARIMA models for countries HCPI.				
	Difference order	**Constant**	**ARIMA structure**	**Seasonal Dummies**
Germany	1	0.0009	White noise	yes
France	1	---	White noise	yes
Spain	1	0.002	$1/(1-0.41L)a_t$	yes
Italy	1	0.0018	$1/(1-0.12L-0.49L^2)\ a_t$	yes

Table 7 shows the standard residual deviations with degrees of freedom correction from the VEqCM and ARIMA models.

Table 7: Standard residual deviations		
	VEqCM	**Univariate ARIMA**
Germany	0.17%	0.15%
France	0.17%	0.18%
Spain	0.16%	0.14%
Italy	0.09%	0.10%

Note that in the univariante model for Italy enters a second lag of its first difference. The VEqCM was reestimated in order to introduce this lag but the result obtained showed that the coefficient corresponding to it was not significant in any equation of the VEqCM.

2.2 Analysis by sectors

The breakdown of HCPI by markets has been approached taking into account the price indexes corresponding to: (1) Processed Food (PF), (2) Non-Energy Commodities excluding food (COM), (3) Non-Energy Services (SER), (4) Non Processed Food (NPF) and (5) Energy (ENE). Espasa et al. (1987) proposed to calculate for Spain core inflation from PF, COM and SER and this practice has also been adopted later for MU. With the NPF and ENE we can calculate an inflation measure denoted as "residual inflation".

Table 8 shows the weights for different MU sectors in the calculation of HCPI, corresponding to year 2000.

Table 8: Sectors weights in MU	
Sectors	**Weight (2000)**
Core Inflation	**82.820%**
Processed Food (PF)	12.645%
Non-Energy Commodities (COM)	32.663%
Non-Energy Services (SER)	37.512%
Residual Inflation	**17.173%**
Non-Processed Food (NPF)	8.209%
Energy (ENE)	8.964%
Global	**100%**
Source: Eurostat	

Graphs of the five indexes can be found in figures 3 A and 3 B.

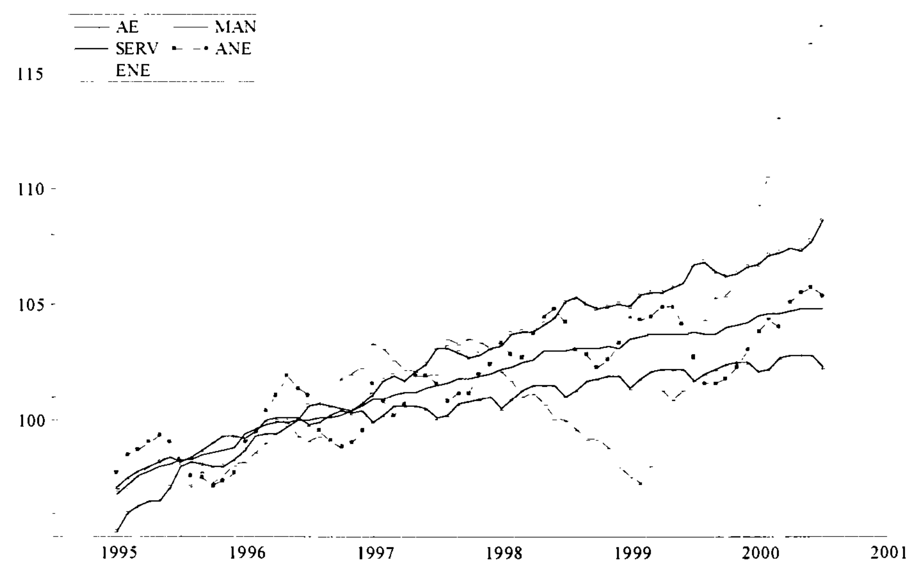


Figure 3 A: Different MU Harmonised Consumer Price Indexes sectors.
Source: Eurostat

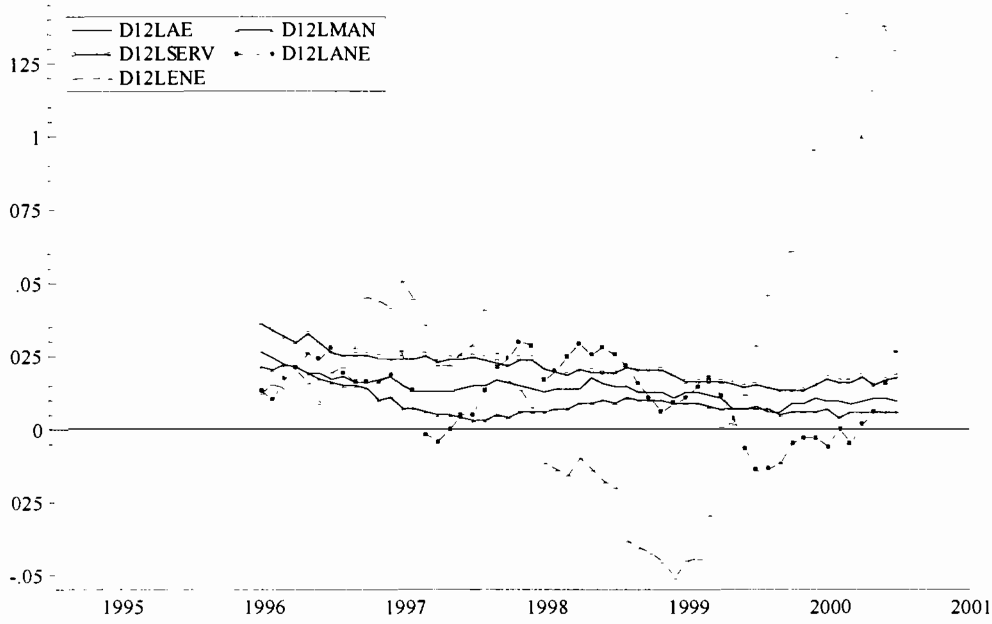


Figure 3 B: HCPI sectors annual rates of growth (seasonal difference in logs).
Source: Eurostat

As before, it is useful to determine the orders of integration for the variables considered. Table 9 lists augmented Dickey-Fuller (1981) (ADF) statistics for these variables.

Table 9: ADF statistics for testing for a unit root

Null Order	PF	COM	SER	NPF	ENE
I(1)	-1.68 (-0.03)	-0.44 (-0.01)	-0.80 (-0.01)	-1.47 (-0.07)	1.14 (0.06)
I(2)	-4.08** (-1.18)	-4.48** (-1.52)	-5.61** (-1.51)	-3.74** (-0.63)	-3.86** (-0.69)

Notes: (1) Here and elsewhere in this paper, asterisks * and ** denote rejection at the 5% and 1% critical values. The critical values for this table are calculated from MacKinnon (1991). Constant and seasonal dummies have been included in the regression.

(2)The results here presented are obtained from PC-GIVE 9.0

(3) Series are taken in logs.

(4) Values reported are the first order (k=1) augmented Dickey-Fuller statistics for PF, COM and SER; Dickey-Fuller statistics for NPF and ENE; and in parentheses the estimated coefficient on the lagged variable x_{t-1}

Unit root tests are reported for the original variables in logs and for their first differences. Empirically, all variables appear to be integrated of order 1 (I(1)) and the hypothesis of a second unit root is rejected.

The cointegration analysis began with a VAR model in levels of order 5 with a constant term and seasonal dummies which then has been reduced to a first-order VAR (Table A4 in appendix shows that it is statistically acceptable).

Table 10 reports the standard statistics and estimates for Johansen's procedure applied to this firs-order VAR. The greatest eigenvalue and trace eigenvalue statistics (λ_{max} and λ_{trace}) reject the null of no cointegration in favour of at least one cointegrating relationship.

Table 10: A cointegration analysis of global HCPI by sectors.

Eigenvalue	0.52	0.39	0.15	0.08	0.02
Null Hypotesis	r=0	r≤1	r≤2	r≤3	r≤4
λ_{max}	43.2**	29.04*	9.92	5.22	1.13
λ_{max}^{a}	39.54**	26.58	9.08	4.78	1.03
95% critical value	33.5	27.1	21.0	14.1	3.8
λ_{trace}	88.51**	45.31	16.27	6.35	1.13
λ_{trace}^{a}	81.01**	41.47	14.89	5.81	1.03
95% critical value	68.5	47.2	29.7	15.4	3.8
		Standardized eigenvectors β'			
Variable	PF	COM	SER	NPF	ENE
	1.00	-0.24	-0.49	-0.12	-0.00
	6.72	1	-4.10	-0.67	-0.05
	-0.89	0.08	1.00	-0.63	-0.11
	-3.34	19.14	-7.72	1.00	2.15
	2.86	-7.75	1.66	-0.64	1.00
		Weak exogeneity test statistics			
Variable	PF	COM	SER	NPF	ENE
$\chi^2(1)$	0.0998	8.867**	9.889**	9.464**	0.1143
p-value	0.7521	0.0029	0.0017	0.0021	0.7353

Figure 4 shows the cointegration vector corresponding to the estimation of the greatest eigenvalue.

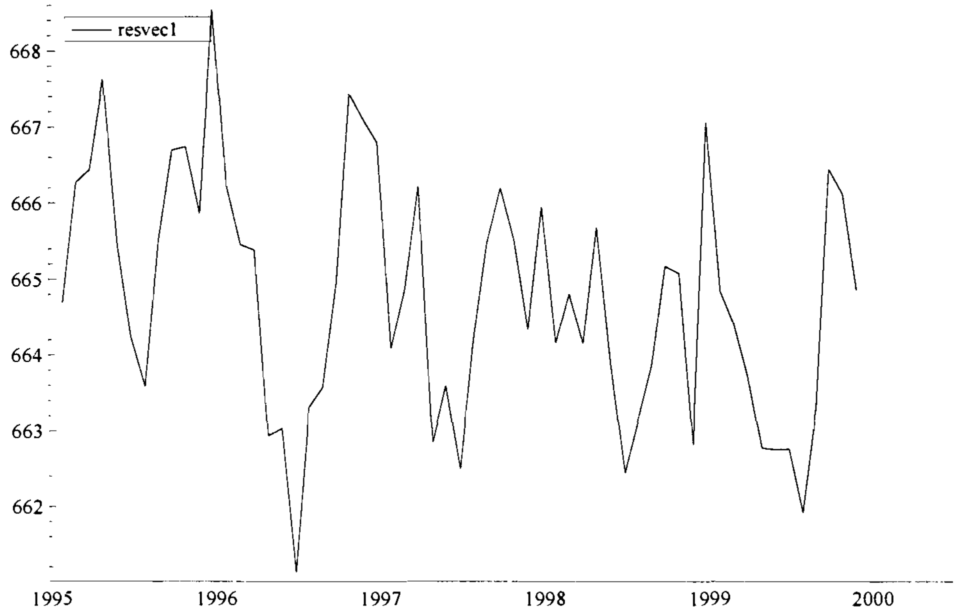


Figure 4: Cointegration relationship corresponding to the greatest eigenvalue

The previous analysis indicates the lack of full cointegration between HCPI sectors and, therefore, the existence of more than one single common trend between them. These type of results appear also for specific countries -see Espasa et al. (1999)- and favour the argument that monetary policy is not the unique, perhaps the most important one, factor determining the long run behaviour in prices. They point out that there are other factors affecting the trend of prices in the different sectors of the economy, possibly different ways and degrees in incorporating technical innovations, different ways in improving the quality of the goods and services produced, etc. This last factor could be important because qualitative improvements generate an upward bias in the usual measures of prices employed in the construction of consumer price indexes and this bias could have very different profile across sectors.

The estimated cointegration relationship can be written as:

$$1.96 \log (PF) = 0.51 \log (COM) + \log(SERV) + 0.20 \log(NPF)$$

A Vector Autoregression Model with Equilibrium-Correction Mechanism for the five sectors has been estimated and results are shown in table 11. The model also includes seasonal dummies and CI_t represents the cointegration relationship.

Table 11: VEqCM model for sectors.

$$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1+0.25L & 0 & 0.08L & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1-0.29L & 0 \\ 0 & 0 & 0 & 0 & 1-0.42L \end{pmatrix} \begin{pmatrix} \Delta \log PF_t \\ \Delta \log COM_t \\ \Delta \log SER_t \\ \Delta \log NPF_t \\ \Delta \log ENE_t \end{pmatrix} - \begin{pmatrix} 0.001 \\ -0.32 \\ -0.36 \\ 0.007 \\ 0.01 \end{pmatrix} - \begin{pmatrix} 0 \\ 0.51L \\ 0.58L \\ 0 \\ 0 \end{pmatrix} CI_t = \begin{pmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \\ a_{4t} \\ a_{5t} \end{pmatrix}$$

The residual standard deviation for each equation is shown in table 14 and the correlation matrix for the residuals is:

Table 12: Correlation matrix of residuals

	Δlog PF	Δlog COM	Δlog SER	Δlog NPF	Δlog ENE
Δlog PF	1.00				
Δlog COM	0.35	1.00			
Δlog SER	0.28	0.05	1.00		
Δlog NPF	0.05	-0.12	-0.11	1.00	
Δlog ENE	-0.10	-0.26	0.03	0.09	1.00

This model shows (1) there is just one long run equilibrium equation that only enters in the Non Energy Commodities and Services equations (2) there is less contemporaneous correlation between the residuals than in the breakdown by countries and (3) as it can be confirmed by the cross-correlograms of the residuals there is not much dependency among the variables in the short-run. The presence of the equilibrium mechanism in two equations indicates that the analysis by single-equation models for each sector is not efficient. Nevertheless, the single-equation approach is much simpler to implement in order to forecast and we have also estimate univariate ARIMA models for the sector price indexes. They are summarised in table 13.

Table 13: Univariate ARIMA models for sectors.

	Difference order	Constant	ARIMA structure	Seasonal Dummies
PF	1	0.0012	white noise	---
COM	1	0.0008	$(1+0.44L^2)\, a_t$	yes
SER	1	0.0019	$(1+0.49L^4)a_t$	yes
NPF	1	0.0009	$1/(1-0.33L)(1+0.36L^{12})a_t$	yes
ENE	1	0.0019	$1/(1-0.30L)a_t$	---

Table 14 shows the standard residual deviations with degrees of freedom correction in both approaches.

Table 14: Standard residual deviations		
	VEqCM	**Univariate ARIMA**
PF	0.11%	0.13%
COM	0.09%	0.09%
SER	0.10%	0.11%
NPF	0.38%	0.31%
ENE	0.74%	0.73%

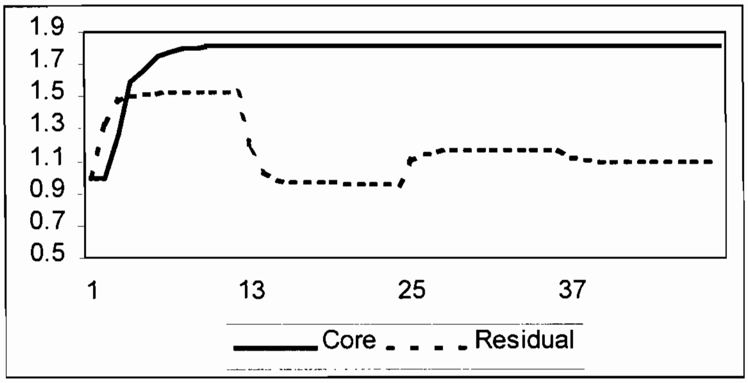
2.3 Conclusions

The results obtained for countries and for sectors imply that if in a particular month the innovation in the HCPI is coming mainly from a given country or sector it will have a long-run effect which will differ from the one corresponding to an innovation in another month which refers mainly to a different country o sector. The question is that aggregating n non-stationary time series, the resulting ARIMA model for the aggregate can have a quite complex structure with important restrictions and it turns to be almost impossible to discover such specification from the analysis of the aggregate data only. Consequently an usual parsimonious unrestricted univariate model, say ARIMA, will not be adequate for the aggregate. Evidence for that can be found in the fact that for a huge number of macroeconomic time series after estimating univariate ARIMA models a certain number of outliers appear (see, for instance, Balke and Fomby (1994)). This evidence also points out that even the linearity hypothesis could not be appropriate. In that respect Senra (1998) shows that an ARIMA model with innovative outliers can be represented as a model with stochastic unit roots and in those models the innovation response function change with time. In this paper we restrict ourselves to linear formulations, but the necessity of nonlinear models is more clear at the disaggregate level, for instance, in modelling certain energy consumer prices.

The previous discussion points out that when the n time series which compound a given aggregate are not fully cointegrated it is advisable to work with the components, provided we have good disaggregated data and it turns possible to obtain reasonably acceptable models for the components. In this section, it has been shown that the European inflation does not show full cointegration by countries, nor by sectors and then it is going to pay to analyse this inflation in a disaggregated way.

Certainly this breakdown of a vector variable like CPI when there is not full cointegration is important for diagnosis purposes, because for instance, it has not the same implications an innovation, properly weighted, from services prices than from non-processed food prices. In fact, institutions which each month analyse inflation alert from time to time the readers saying that a high surprise on inflation in a given month is particularly worrying because it comes from prices included in the core inflation. In other cases such institutions could say for an innovation of the same magnitude in the CPI that it is not particularly important because it comes from the set of prices corresponding to the residual inflation. To illustrate this point, figure 5 shows the impact multipliers, which are the response function to an innovation in core and residual inflation. The effect of an innovation in core inflation settles gradually on 1,8 times the value of the innovation. On the other hand, an innovation in residual inflation will have an oscillate impact that will stabilise at around 1,1 times the value of the innovation.

Figure 5: Response function to an innovation in the price indexes for core and residual inflation.



3. Forecasting MU inflation

This section evaluates the forecast performance of the univariate and multivariate models proposed in section 2, and compares them with an univariate ARIMA aggregate model for the Monetary Union HCPI.

The univariate ARIMA model for the Monetary Union HCPI has been also estimated with information from January 1995 to December 1999 and the results obtained are:

$$\Delta \log HCPI_t = 0.0013 + 1/(1\text{-}0.85L)\, a_t \qquad (1)$$

The model also includes seasonal dummies and has a standard residual deviation of 0.098%.

Table 15 shows the statistics related to the errors in forecasting inflation rate of growth in the MU 1, 2 and 3 periods ahead from January 2000 to July 2000 . The forecasts have been done (a) using the aggregate model (1), (b) VEqCM model by countries in table (4), (c) VEqCM model by sectors in table (11), (d) univariate country models in table (6), and (e) univariate sector models in table (13). In cases (b) and (d) the forecasts of the MU aggregate has been obtained using in both cases univariate ARIMA models for the remaining seven countries that have not been considered in section 2.

Table 15: Forecast performance, period 2000 (1) to 2000 (7)				
		Periods ahead		
		1	2	3
Mean Error	MU univ. aggregate	0.07	0.16	0.20
	MU sectorial aggregation (univ.)	-0.04	0.03	0.06
	MU sectorial aggregation (VEqCM)	0.01	0.10	0.14
	MU country aggregation (univ.)	0.06	0.18	0.24
	MU country aggregation (VEqCM)	0.13	0.32	0.47
Mean Absolute Error	MU univ. aggregate	0.12	0.22	0.20
	MU sectorial aggregation (univ.)	0.12	0.14	0.10
	MU sectorial aggregation(VEqCM)	0.10	0.22	0.20
	MU country aggregation (univ.)	0.13	0.25	0.24
	MU country aggregation (VEqCM)	0.15	0.33	0.47
Root Mean Squared Error	MU univ. aggregate	0.17	0.28	0.24
	MU sectorial aggregation (univ.)	0.13	0.18	0.12
	MU sectorial aggregation (VEqCM)	0.13	0.28	0.30
	MU country aggregation (univ.)	0.17	0.29	0.29
	MU country aggregation (VEqCM)	0.20	0.38	0.49

According to table 15 there is a clear gain in forecasting HCPI by considering a disaggregated sectorial approach, with the univariate sector models given for this short period better forecasts than the corresponding VEqCM model.

A second forecasting exercise has been performed comparing the forecasts of the univariate aggregated model with the ones from the univariate sector models and VEqCM models for a wider forecasting period, January 1999 to July 2000. Univariate models were reestimated with information up to December 1998, but for the VEqCM model the estimation of table (11) with information till December 1999 has been used. This second exercise allows to evaluate the forecast performance up to twelve periods ahead.

Table 16: Forecast performance, period 1999 (1) to 2000 (7)						
		Periods ahead				
		1	2	3	6	12
Mean Error	MU univ. aggregate	0.03	0.09	0.12	0.24	0.50
	MU sectorial aggregation (univ.)	-0.03	0.02	0.05	0.15	0.39
	MU sectorial aggregation (VEqCM)	-0.01	0.04	0.08	0.16	0.34
Mean Absolute Error	MU univ. aggregate	0.12	0.20	0.17	0.28	0.50
	MU sectorial aggregation (univ.)	0.11	0.14	0.14	0.22	0.39
	MU sectorial aggregation (VEqCM)	0.08	0.13	0.12	0.20	0.38
Root Mean Squared Error	MU univ. aggregate	0.15	0.23	0.20	0.33	0.54
	MU sectorial aggregation (univ.)	0.14	0.17	0.16	0.24	0.43
	MU sectorial aggregation (VEqCM)	0.10	0.18	0.19	0.27	0.47

The results in table 16 show again the better performance of disaggregating HCPI against an univariate aggregated alternative. In particular, when regarding 12 months ahead forecasts this table shows that the disaggregated modelling not only produces smaller bias but also a smaller confidence interval. The 95% confidence interval for 12 months ahead forecasts with the univariate model has a width of 2.16 percentage points, while with the disaggregated approach it is only 1.72 percentage points.

Figures 6 and 7 show the MU annual inflation rates forecast paths for the next twelve months by means of the univariate models by sectors and by a single univariate model for the aggregate. These figures show the forecast paths generated with information available up to the date specified by the legend of the line.

Figure 6: MU annual inflation forecast paths by means of univariate models by sectors

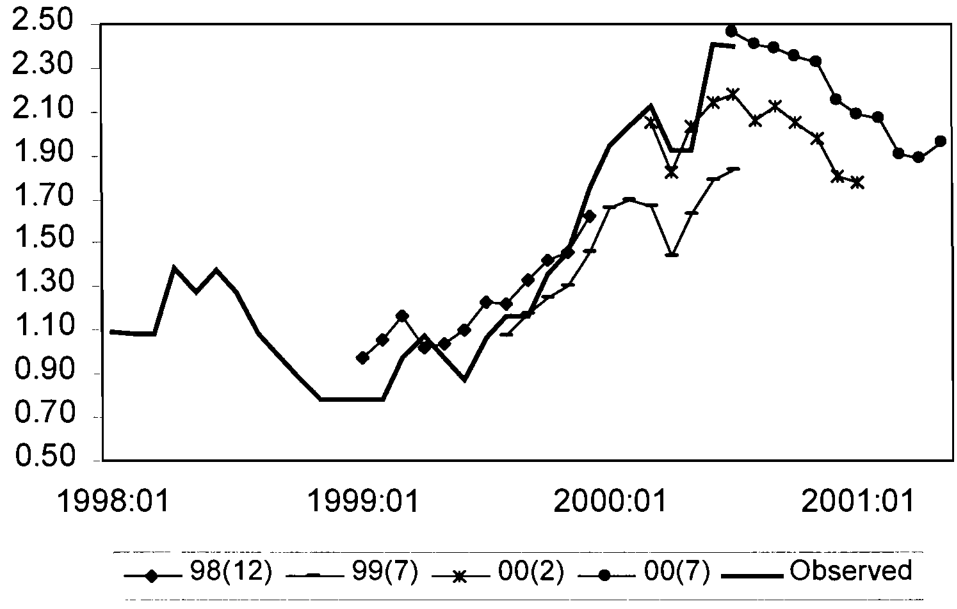
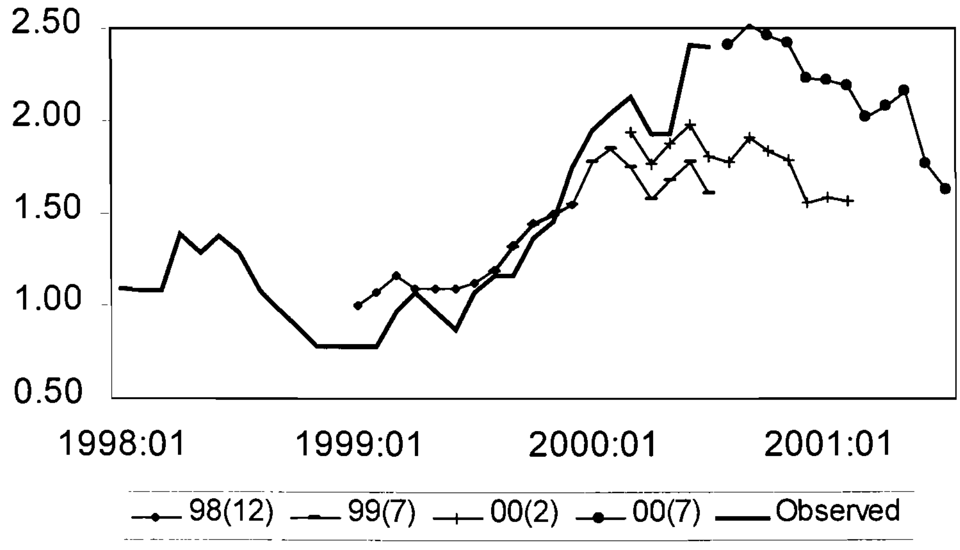


Figure 7: MU annual inflation rates forecast paths by means of a univariate aggregate model



These figures illustrate how in a moment of low inflation as December 1998, both approaches were able to capture the recovery of inflation along 1999. But for the posterior increases is the disaggregated approach the one which shows a better performance. These results point out that disaggregating helps to minimize forecasts errors and even a greater disaggregation by markets could be useful. As an example, in the monthly forecasts for MU inflation provided by the Bulletin EU & US Inflation and Macroeconomic Analysis published by the University Carlos III (Madrid), this option has already been explored and a further disaggregation dividing the energy price index in three components, gas and electricity, fuels and motor oils, gives much better results in periods with unstable international crude prices.

Tables 17-20 show a forecasting performance exercise in each of the four analysed countries through the univariate model for the HCPI in each country and the VEqCM model.

Table 17: Forecast performance for HCPI Germany, period 2000 (1) to 2000 (7)				
		1	2	3
Mean Error	univariate.	0.10	0.16	0.15
	Country VEqCM	0.27	0.51	0.67
Mean Absolute Error	univariate.	0.23	0.30	0.24
	Country VeqCM	0.31	0.54	0.67
Root Mean Squared Error	univariate.	0.27	0.37	0.29
	country VeqCM	0.37	0.61	0.71

Table 18: Forecast performance for HCPI France, period 2000 (1) to 2000 (7)				
		1	2	3
Mean Error	univariate	0.15	0.30	0.45
	country VEqCM	0.11	0.23	0.34
Mean Absolute Error	univariate	0.18	0.30	0.45
	country VEqCM	0.17	0.23	0.34
Root Mean Squared Error	univariate	0.22	0.36	0.48
	country VEqCM	0.19	0.30	0.39

Table 19: Forecast performance for HCPI Italy, period 2000 (1) to 2000 (7)				
		1	2	3
Mean Error	univariate	0.05	0.10	0.10
	country VEqCM	0.05	0.12	0.22
Mean Absolute Error	univariate	0.13	0.23	0.19
	country VEqCM	0.12	0.19	0.22
Root Mean Squared Error	univariate	0.16	0.25	0.24
	country VEqCM	0.14	0.21	0.26

Table 20: Forecast performance for HCPI Spain, period 2000 (1) to 2000 (7)				
		1	2	3
Mean Error	univariate	0.12	0.27	0.37
	country VEqCM	0.29	0.63	0.96
Mean Absolute Error	univariate	0.13	0.27	0.37
	country VEqCM	0.29	0.63	0.96
Root Mean Squared Error	univariate	0.16	0.34	0.42
	country VEqCM	0.31	0.66	0.98

For Germany and Spain the VEqCM model gives higher RMSE than univariate models and the opposite is true for France and Italy. It must be noted that in the VEqCM model in the equation corresponding to Italy includes the cointegrating vector.

4. Diagnosis and Forecasts of the MU inflation for 2000 and 2001 and some concluding remarks.

The analysis of European inflation by countries and by sectors shows that there is not full cointegration in either case, therefore disaggregation matters. From a forecasting point of view the breakdown by sectors generates forecasts with smaller bias and variance at all horizons showing the interest of disaggregating also for the purpose of just forecasting the European aggregate.

The above results and the fact that the CPI by countries are not fully cointegrated suggest that a breakdown of the European CPI applying jointly the sector and country criteria will produce further improvements in forecasting.

In the paper it has been mentioned that the revisions by Eurostat of the CPI data by sector are greater and happen more often than the revisions for the aggregated CPI of individual countries. The results of this paper show the importance that it has for the study of European inflation that Eurostat improves the quality of consumer prices by sectors in every country.

Table 21 below collected from the monthly publication Bulletin EU & US Inflation and Macroeconomic Analysis, can be used as an example of how disaggregated forecasts can employed for diagnosis purposes.

TABLE 21: AVERAGE ANNUAL RATES OF GROWTH

	OBSERVED		FORECASTS	
	1998	1999	2000	2001
HCPI GERMANY	0.60	0.64	2.06	1.27
HCPI FRANCE	0.67	0.56	1.82	1.31
HCPI ITALY	1.97	1.65	2.56	1.90
HCPI SPAIN	1.77	2.23	3.49	3.09
CORE INFLATION	1.41	1.11	1.27	1.60
RESIDUAL INFLATION	-0.35	1.16	7.54	2.51
HCPI MONETARY UNION	1.09	1.12	2.31	1.86

Source: Eurostat & University Carlos III.

The year-on-year inflation rate in the Monetary Union observed in October 2000 was 2.69%, with big differences between the core inflation rate, 1.44%, and a residual inflation, 9.06%. The mean annual rate is predicted to be 2.3% for 2000 and 1.9% for 2001. The core inflation will register a mean annual growth of 1.3% in 2000 and will increase to 1.6% in 2001. Nevertheless, the residual component of the HCPI will reach a mean growth rate of 7.5% in 2000 and it is expected to drop to 2.5% in 2001.

Using a further disaggregated forecast by countries and sectors taken from the available publication it can be seen that inflation differences among countries are important and are not due to the behaviour of energy prices. In fact, in France, Germany, Italy, Spain and MU energy prices showed annual figures not lower than 11%. But the inflation differential among these countries in the Non-energy HCPI is high. While France and Germany will register mean values of between 0.7% and 1.4% in this index throughout 2000 and 2001, Italy will come closer to 1.9% and Spain will reach averages rates of growth of 2.6% and 2.9% in 2000 and 20001 respectively.

It is foreseeable that the above mentioned dispersion will be reduced by a little less than three percentage points in 2001, which means it will continue to be significant. It seems, then, that once the objectives fixed, as criteria for entering the Monetary Union, in the Maastricht Treaty have been achieved, a certain convergency in prices within the Union may have begun. This convergence may be happening in such a way that the countries where price levels are higher are registering inflation levels which are much lower than those of the countries where prices are lower, the consequence of this is that in the latter, the goal of inflation not higher than 2% was achieved in 1999, but it is foreseeable that this will not be the case in 2000. This may mean a change in relative prices between the European economies, which could threaten the greater economic growth that, in general, the Monetary Union countries with greater inflation are showing with respect to those with lower inflation levels. These changes in relative prices will also bring about national specialisation in those sectors in which comparative advantages are enjoyed.

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Appendix

Table A1: Data for sectors and HCPI.
Table A2: Data for countries.
Table A3: Likelihood and Schwarz statistics for the sequential reduction from a fifth-order VAR to a first-order VAR in the analysis by countries.
Table A4: Likelihood and Schwarz statistics for the sequential reduction from a fifth-order VAR to a first-order VAR in the analysis by sectors.

Table A1: Data for sectors						
OBS	PF	COM	SERV	NPF	ENE	HCPI
1995:01	96.8	97.1	95.2	97.7	97	96.7
1995:02	97.2	97.5	96	98.5	97.1	97.1
1995:03	97.6	97.8	96.3	98.7	97.6	97.4
1995:04	97.8	98	96.5	99	98	97.6
1995:05	98	98.2	96.5	99.3	98.3	97.7
1995:06	98.1	98.4	97.1	99	98.4	98.0
1995:07	98.3	98.2	98	98.3	97.2	98.0
1995:08	98.3	98.4	98.2	97.6	97.2	98.1
1995:09	98.5	98.7	98.1	97.5	97.8	98.3
1995:10	98.6	99	98	97.2	97.3	98.4
1995:11	98.7	99.3	98	97.4	97.6	98.5
1995:12	98.8	99.3	98.3	97.7	98.1	98.7
1996:01	99.4	99.2	98.7	99	98.2	98.9
1996:02	99.6	99.5	99.3	99.5	98.6	99.4
1996:03	99.8	100	99.4	100.4	99	99.7
1996:04	99.9	100.1	99.4	101.1	100	99.9
1996:05	99.9	100.1	99.7	101.9	99.9	100.1
1996:06	100	100.1	100	101.4	99.3	100.1
1996:07	100	99.8	100.6	101.1	99.1	100.1
1996:08	100.1	99.9	100.7	99.5	99.3	100.1
1996:09	100.1	100.2	100.6	99.1	100.6	100.3
1996:10	100.2	100.4	100.5	98.8	101.8	100.4
1996:11	100.4	100.3	100.4	99	102	100.4
1996:12	100.6	100.4	100.7	99.5	102.3	100.6
1997:01	100.9	99.9	101.1	101.6	103.3	100.9
1997:02	100.9	100.2	101.7	100.8	103.1	101.2
1997:03	101.1	100.6	101.9	100.2	102.6	101.3
1997:04	101.2	100.6	101.7	100.7	102.2	101.2
1997:05	101.2	100.6	102.1	101.9	102.1	101.5
1997:06	101.4	100.5	102.4	101.9	101.9	101.5
1997:07	101.5	100.1	103.1	101.6	102	101.6
1997:08	101.6	100.2	103.1	100.8	103.5	101.8
1997:09	101.8	100.7	102.9	101.2	103.3	101.9
1997:10	101.8	100.8	102.7	101.2	103.5	101.9
1997:11	101.9	100.9	102.8	102	103.4	102.0
1997:12	102	101	103.1	102.4	103.1	102.1
1998:01	102.2	100.5	103.2	103.3	102.1	102.0
1998:02	102.3	100.9	103.7	102.8	101.7	102.3
1998:03	102.5	101.3	103.8	102.7	101	102.4
1998:04	102.6	101.5	103.8	103.7	101.2	102.6
1998:05	103	101.5	104.1	104.5	100.7	102.8
1998:06	103	101.5	104.4	104.8	100.1	102.9
1998:07	103	101	105.1	104.2	100	102.9
1998:08	103.1	101.3	105.3	103	99.6	102.9
1998:09	103.1	101.7	105	102.8	99.2	102.9
1998:10	103.1	101.8	104.8	102.3	99.2	102.8
1998:11	103.2	101.9	104.9	102.6	98.8	102.8
1998:12	103.1	101.9	105	103.3	98	102.9
1999:01	103.5	101.4	104.9	104.4	97.6	102.8
1999:02	103.6	101.8	105.4	104.3	97.3	103.1

1999:03	103.7	102.1	105.5	104.5	98.1	103.4
1999:04	103.7	102.2	105.5	104.9	101.3	103.7
1999:05	103.7	102.2	105.7	104.9	100.9	103.8
1999:06	103.7	102.2	105.9	104.1	101.3	103.8
1999:07	103.8	101.7	106.7	102.7	102.9	104.0
1999:08	103.7	102	106.8	101.6	104.3	104.1
1999:09	103.7	102.2	106.4	101.6	105.3	104.1
1999:10	104	102.4	106.2	101.8	105.4	104.2
1999:11	104.1	102.5	106.3	102.3	105.8	104.3
1999:12	104.2	102.5	106.6	103	107.8	104.7
2000:01	104.5	102.1	106.7	103.8	109.3	104.8
2000:02	104.6	102.2	107.1	104.3	110.5	105.2
2000:03	104.6	102.7	107.2	104	113.1	105.6
2000:04	104.7	102.8	107.4	105.1	111.9	105.7
2000:05	104.8	102.8	107.3	105.5	113.3	105.8
2000:06	104.8	102.8	107.7	105.7	116.3	106.3
2000:07	104.8	102.3	108.6	105.4	117.1	106.5

Table A2: Data for countries				
	Germany	Spain	France	Italy
1995m01	98.1	94.9	97	93.3
1995m02	98.6	95.3	97.3	94
1995m03	98.6	95.9	97.5	94.8
1995m04	98.7	96.4	97.7	95.3
1995m05	98.7	96.4	97.8	95.9
1995m06	99	96.5	97.8	96.5
1995m07	99.2	96.5	97.6	96.7
1995m08	99.1	96.8	98.1	96.9
1995m09	99	97.2	98.5	97.2
1995m10	98.8	97.3	98.6	97.5
1995m11	98.8	97.6	98.7	98.1
1995m12	99.1	97.9	98.8	98.2
1996m01	99.2	98.5	98.9	98.6
1996m02	99.8	98.7	99.3	99
1996m03	99.9	99.1	100	99.3
1996m04	99.8	99.7	100.1	99.7
1996m05	100	100.1	100.3	100.1
1996m06	100.1	100	100.2	100.3
1996m07	100.3	100.1	100	100.2
1996m08	100.2	100.4	99.8	100.3
1996m09	100.2	100.7	100.1	100.4
1996m10	100.1	100.8	100.4	100.5
1996m11	100	100.8	100.3	100.9
1996m12	100.4	101.1	100.5	101
1997m01	101	101.3	100.7	101.2
1997m02	101.4	101.2	101	101.3
1997m03	101.3	101.3	101.1	101.5
1997m04	101	101.3	101.1	101.6
1997m05	101.4	101.4	101.2	101.9
1997m06	101.6	101.4	101.2	101.9
1997m07	101.9	101.6	101.1	101.9
1997m08	102	102.1	101.4	101.9
1997m09	101.7	102.6	101.6	102
1997m10	101.6	102.6	101.5	102.4
1997m11	101.6	102.7	101.7	102.7
1997m12	101.8	103	101.7	102.8
1998m01	101.7	103.2	101.3	103.1
1998m02	102	102.9	101.7	103.4
1998m03	101.8	103	101.9	103.6
1998m04	101.9	103.2	102.1	103.8
1998m05	102.3	103.4	102.2	103.9
1998m06	102.4	103.4	102.3	104
1998m07	102.7	103.9	101.9	104
1998m08	102.6	104.2	102	104.1
1998m09	102.2	104.2	102.1	104.1
1998m10	102	104.2	102	104.3
1998m11	102	104.1	101.9	104.4
1998m12	102	104.4	102	104.5
1999m01	101.9	104.7	101.6	104.6

1999m02	102.1	104.8	102	104.8
1999m03	102.3	105.2	102.3	105
1999m04	102.7	105.6	102.6	105.2
1999m05	102.7	105.6	102.6	105.5
1999m06	102.8	105.6	102.6	105.5
1999m07	103.3	106.1	102.3	105.8
1999m08	103.3	106.6	102.5	105.8
1999m09	103	106.8	102.7	106.1
1999m10	102.9	106.7	102.8	106.3
1999m11	103	106.9	102.9	106.5
1999m12	103.4	107.3	103.4	106.7
2000m01	103.8	107.7	103.3	106.9
2000m02	104.2	107.9	103.5	107.3
2000m03	104.4	108.4	104	107.7
2000m04	104.3	108.8	104	107.7
2000m05	104.2	109	104.2	108.1
2000m06	104.9	109.3	104.5	108.4
2000m07	105.4	110	104.3	108.6

Table A3: Sequential Reduction from the Fifth-order VAR to the First-order VAR for countries			
System	k	£	SC
VAR(5)	128	1549.4	-47.01
VAR(4)	112	1541.2	-47.88
VAR(3)	96	1534.9	-48.82
VAR(2)	80	1516.3	-49.31
VAR(1)	64	1492.4	-49.61

Notes:
(1) For each system, the columns report: the number of unrestricted parameters, k, the log- likelihood £, and the Schwarz criterion (SC).
(2) A smaller SC indicates a better-fitting model for a given number of parameters. The SC becomes more negative as the lag length is shortened.

Table A4: Sequential Reduction from the Fifth-order VAR to the First-order VAR for sectors			
System	k	£	SC
VAR(5)	185	1915.2	-56.2
VAR(4)	160	1866.3	-56.2
VAR(3)	135	1825.3	-56.5
VAR(2)	110	1794.8	-57.2
VAR(1)	85	1768.9	-58.1

Notes:
(1) For each system, the columns report: the number of unrestricted parameters, k, the log- likelihood £, and the Schwarz criterion (SC).
(2) A smaller SC indicates a better-fitting model for a given number of parameters. The SC becomes more negative as the lag length is shortened.